PARTICLE SWARM OPTIMIZATION AND DIFFERENTIAL EVOLUTION ALGORITHM FOR ENERGY MANAGEMENT

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OF

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IN
POWER SYSTEM

SUBMITTED BY

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I, **Amisha Srivastava**, Roll No. **2K20/PSY/03**, M.Tech. (Power Systems), hereby declare that the project Dissertation titled "**PARTICLE SWARM OPTIMIZATION AND DIFFERENTIAL EVOLUTION ALGORITHM FOR ENERGY MANAGEMENT**" which is submitted by me to the Department of Electrical Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is not imitated from any source without proper citation and is authentic. This work has not beforehand formed the root for the award of any Degree, Diploma, Fellowship, Associateship or any other similar title or acknowledgment.

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CERTIFICATE

I, hereby certify that the Project Dissertation titled "**PARTICLE SWARM OPTIMIZATION AND DIFFERENTIAL EVOLUTION ALGORITHM FOR ENERGY MANAGEMENT**" which is submitted by **Amisha Srivastava**, Roll No. **2K20/PSY/03,** Department of Electrical Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology is a testimony of the project work carried out by the student under our supervision. To the best of our awareness this work has not been submitted in part or full for any Degree or Diploma to this University or to a different place.

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ABSTRACT

The transition of conventional electric grid to smart grid brings with it many concerns and challenges. One such challenge is efficient and smart usage of energy. Energy Management System (EMS) combining both hardware and software is intended at minimizing energy wastage, reduce cost and thus provide eco-friendly solutions. It is a collection of computerized tools used to monitor, control, and optimize the system performance. Various aspects of energy management are home energy management system, building energy management system, advanced metering infrastructure, electric vehicle and demand side energy management system. Home energy management system, building energy management system or grid energy management system acts as interface between energy suppliers and consumers. Efficient use of energy at grid level and end-user level is achieved with advanced metering infrastructure. Initial development of EMS could not incorporate the introduction of Electric Vehicles; however with the design of multi-level EMS it is made possible. EMS together with Internet of Things, Machine Learning/Artificial Neural Network can provide best solutions for economic development.

Use of several stochastic and deterministic algorithms for the purpose of energy management has rapidly gained substantial importance recently owing to their flexibility, ease of implementation and efficient results. The present work makes use of two algorithms based on Particle Swarm Optimization (PSO) and Differential Evolution (DE) algorithm for optimizing consumption of power using smart energy meter data analytics. Both are meta-heuristic algorithms that can easily solve multifaceted problems in engineering. The power consumption equation has been optimized using first PSO then DE. The validity and efficiency of the algorithm is tested using the real time data obtained from smart energy meter and a comparative study is presented. The modeling and simulation is carried on MATLAB platform and the results depict that both presented algorithms can ominously reduce the power consumption. With PSO approximately 11.5% reduction in power can be obtained and DE can reduce up to 9.4% power in best-case scenario making PSO superior to DE.

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LIST OF ABBREVIATIONS

AMI	Advanced Metering Infrastructure
BEMS	Building Energy Management System
DE	Differential Evolution
DR	Demand Response
DSM	Demand Side Management
EMS	Energy Management System
EV	Electric Vehicles
ICT	Intelligent Control Techniques
PSO	Particle Swarm Optimization
SEM	Smart Energy Meter
SHEMS	Smart Home Energy Management System
SG	Smart Grid

LIST OF SYMBOLS

Np	Population size of algorithm
λ	Coefficient of constraint violation
P_{lb}	Local best of particles in PSO
P_{gb}	Global best of particles in PSO
n	Generation number
α_1	Acceleration coefficient
α_2	Social coefficient
ω	Inertia of particles in PSO
r_1, r_2	Random numbers
C_R	Crossover rate in DE
f	Differential weight in DE

CHAPTER 1
INTRODUCTION

1.1 Background of Research

The blooming smart technology has improved the living standard of people in most part of the world and with that the energy consumption pattern has drastically changed. Furthermore, it is estimated that the world's population by the end of 2050 would be around 9.8 billion [1]. Such surge in population escalates the energy consumption which may globally rise to 25% by 2040 [2]. With the escalating dependence of human life style on energy, the need for technological advancement with innovative solution for sustainable energy consumption becomes significant. Researchers have now shifted their concern towards devising tools that minimizes energy loss and use it proficiently. Energy Management System (EMS) is one such tool and is defined as the combination of all the hardware and software that are collectively used to minimize energy wastage and provide a sustainable solution to energy saving.

India is the third leading producer of electricity in the world owing to continued industrialization and urbanization [3]. With such a colossal production, the consumption of electricity is equally massive and its appropriate management is a big challenge. Modern power system with transformation of conventional grid into smart grid is one big step towards energy management. Smart grid facilitates real time monitoring and control, advanced metering infrastructure via Smart Energy Meters (SEM), demand response control and power optimization tools [4]. Smart Grid and EMS go hand in hand. Multiple features of smart grid like bi-directional communication between producer and consumer, transparent energy transmission system, eco-friendly environment etc. are achieved to a great extent using EMS. The Smart Home Energy Management System (SHEMS) and Building Energy Management System (BEMS) are the emerging areas in energy management. Many software and devices have been designed to make smart homes and reduce electricity bills in big industries. The most important component of HEMS and BEMS is the Advanced Metering Infrastructure (AMI). AMI has been adopted by a large number of countries worldwide. Smart meters unlike manual meters provide real-time monitoring and also facilitate bi-directional communication for consumers. Electric Vehicles (EVs) have gain significant importance in recent years and their role in Smart Grid cannot be neglected. EVs are true solution for reducing greenhouse gases. Studies reveal that researchers are developing interests towards Demand Response (DR) Program. DR is primarily concerned with adjusting demand according to supply instead of adjusting supply according to demand. It allows consumers to actively participate in energy saving and is cost-effective. SEMs provide efficient billing and allow users to use electricity responsibly [5]. Likewise, application of optimization techniques in solving complex and real-world engineering problems is for all intents and purposes used to obtain the optimum solution.

1.2 Overview of Optimization Techniques

Optimization is a process that forms an essential component of daily life. In the most fundamental sense, it can be defined as a process of finding the finest way to use existing resources, while at the same time not violating any of the constraints that might subsist [6]. The optimization process involves a number of steps: mathematical definition of a system, identifying its variables and the set of certain conditions that they must satisfy, definition of the properties of the system, and then inspecting out the state of the system (that is, the values of the variables) that gives the desirable properties, either maximum value or minimum value. Throughout the years, numerous approaches have been proposed to carry out the optimization. Most of these approaches are based on classical methods, like the Sequential Unconstrained Minimization Technique, Newton-Raphson, the Successive Quadratic Programming algorithm, the Augmented Lagrangian, Dynamic and Integer Programming, and the Stochastic Newton optimization method [7]. Conventional methods such as Linear Programming and Nonlinear Programming are well-organized approaches that can be implemented to solve special cases of optimization problem in power system applications [8]. However, there is a drawback of these techniques that they are not well applicable to solve complex optimization problems. As the complexities of the problem amplify, especially with the prologue of uncertainties to the system, more complex optimization techniques that overcome the limitations of classical approaches have to be implemented. Metaheuristic methods have been developed with keeping this purpose in mind.

Fig.1.1 shows the basic overview of what optimization process does. It iteratively tries to converge the solution to one global optimal value whether maximum or minimum as defined in the problem.

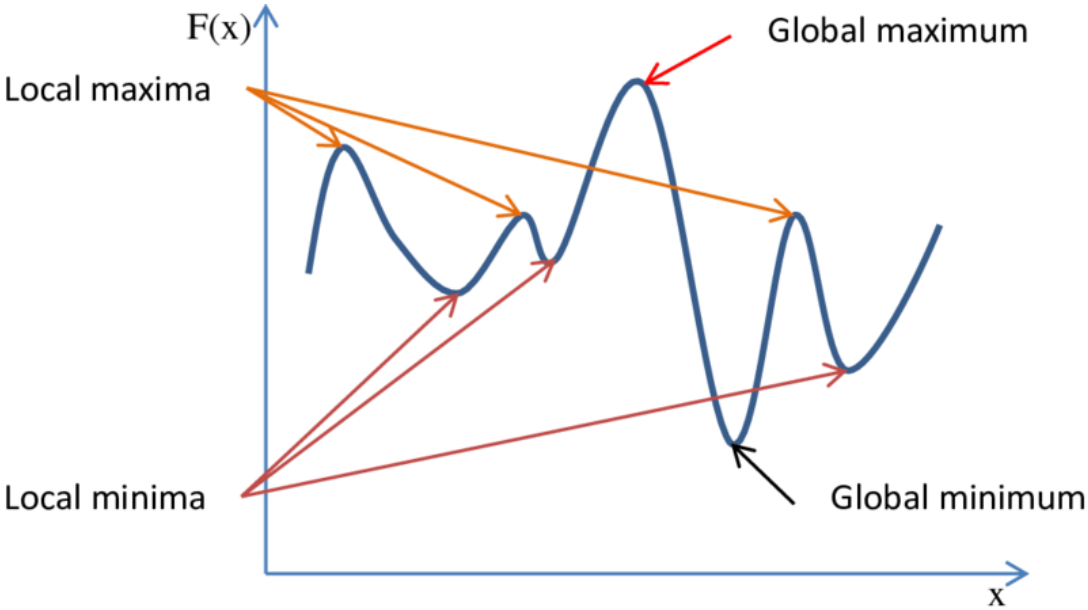

Fig.1.1 Optimization Process

1.3 Application of Optimization Techniques

Optimization techniques have been applied in almost all the fields of power system be it operation, control, planning or analysis. They are applicable on different power system stages such as generation, transmission, distribution and customer's side for minimizing different problems [9].

Some of the major applications of several techniques applied to power system are tabulated in Table 1.1.

Table 1.1 Major applications of optimization techniques

OPERATION	**CONTROL**	**PLANNING**	**ANALYSIS**
Constrained Load Flow	Optimal protection and switching device placement	Reactive power planning	Power system stabilizer
Unit Commitment	Reactive power control	Generation expansion planning	Power plant operation optimizer
Optimal power flow	Power system control	Maintenance planning	Fault Analysis

Short term load forecasting	FACTS(Flexible AC Transmission system control)	Long term load forecasting	State-space analysis
Fault diagnosis	Active power control	Capacitor placement	Generation analysis
Transient stability	Load dispatch	Switchgear planning	Transmission Analysis

1.4 Types of Optimization Techniques

The optimization techniques were introduced in early 70s and were applied largely in the field of engineering [10]. The global optimization techniques are classified as deterministic methods or classical methods or heuristic methods and stochastic or meta-heuristic methods [11]. Deterministic methods do not take into account any uncertainties and all inputs are constant which limit their use. Stochastic or meta-heuristic methods however are contingent, flexible i.e. can work with almost all kinds of optimization problems and thus are more popular in real-world problems. Some of the most researched meta-heuristic techniques which are categorized into trajectory based methods and population based methods. Trajectory based methods are less popular as they are used majorly for open-loop solutions for any problem. Population based algorithms on the other hand define an entire set of solutions where each solution corresponds to a unique point in search space.

Among population based algorithms, evolutionary algorithms and algorithms based on swarm intelligence are most popular. Widely used evolutionary algorithms are evolution strategies, genetic algorithm, differential evolution algorithm and estimation of distribution algorithms. Widely used swarm intelligence based algorithms are particle swarm optimization, ant colony optimization, grey wolf optimization, bacterial foraging optimization and BCC algorithm. The entire classification of the optimization techniques is shown in Fig. 1.2. The presented works make use of two algorithms one from each category, Particle Swarm Optimization and Differential Evolution Algorithm and a comparative study is performed.

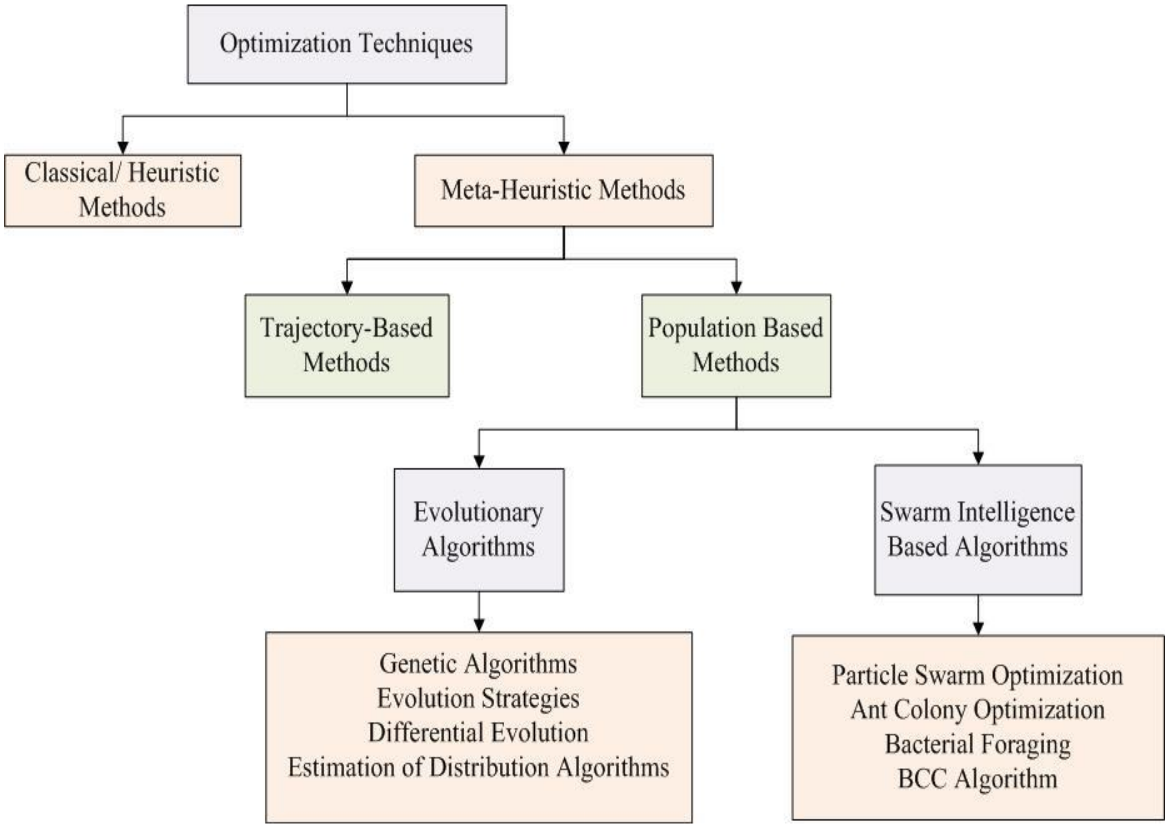

Fig. 1.2 Classification of optimization techniques

1.5 Advantages of Optimization Techniques

Some of the advantages of various optimization techniques applied in solving power system problems are listed below-

- Artificial intelligent methods are applicable to smart grid because of its modernity.
- Some of the algorithms need only coarse information of the objective function and do not place any restraint such as differentiability and continuity on the objective function.
- Optimization techniques work with a set of solutions from one generation to the next, and not a solitary solution, thus making it very less likely to converge on local minima.
- In genetic algorithm or differential evolution algorithm the solutions developed are randomly based on the probability rate of the genetic operators such as mutation and crossover; the initial solutions thus would not dictate the search direction of algorithms.
- Optimization algorithms are easy to compute, design and implement.

- They are efficient in dealing with large scale datasets and require comparatively less memory as they do not store the previous values.
- Fuzzy logic more precisely represents the operational constraints of power systems and fuzzified constraints are softer than traditional constraints which promote its application in many areas.
- The further advantages of these techniques are general applicability to deal with uninformed or arbitrary systems and cost functions, their ability to refine optimal solution, and the simplicity of implementation even for very complex problems.

1.6 Disadvantages of optimization techniques

Besides all the advantages that optimization techniques have, there are certain limitations that cannot be neglected. Some of them are listed below-

- Solution need to be updated continuously.
- Sometimes due to pre-mature convergence, solution can be far from optimal.
- In some algorithms, the hyper-parameters required are large with effect the efficiency of the algorithm.

1.7 Outline of Dissertation

This dissertation is divided into five chapters including this chapter. The summary of various chapters is given below-

Chapter 1. This chapter is the introduction wherein background of the research area is described and a general overview of the optimization process, their categorization, applications, advantages and disadvantages are listed in great details.

Chapter 2. This chapter gives the literature review of related works. Various literatures related to energy management system, the classification into smart home energy management system, building energy management system, advanced metering infrastructure, EMS in electric vehicles and demand side energy management system is explained in a structured way to give in depth knowledge of Energy Management System and its various aspects.

Chapter 3. Third chapter presents the mathematical modeling of the two algorithms namely Particle Swarm Optimization algorithm and Differential Evolution Algorithm, their working in the form of flowcharts and explanation about the models. It also describes the methodology of the presented work.

Chapter 4. Fourth chapter shows the results obtained by two algorithms, tabular representation of various data obtained from smart energy meter and multiple settings of parameters of the two algorithms. A comparative analysis between the two algorithms is also described.

Chapter 5. In the last chapter a conclusion of the work is presented and various future aspects of the work that can be implemented are described.

CHAPTER 2
LITERATURE REVIEW

EMS is designed with compound techno-economical objectives that are implemented at various levels. These objectives include minimizing electricity bills, maintenance cost, power losses, maintaining stability, handling frequency and voltage deviation at grid level and at the same time maximizing consumer's relaxation [12]. Fig. 2.1 shows various aspects of EMS in smart grid.

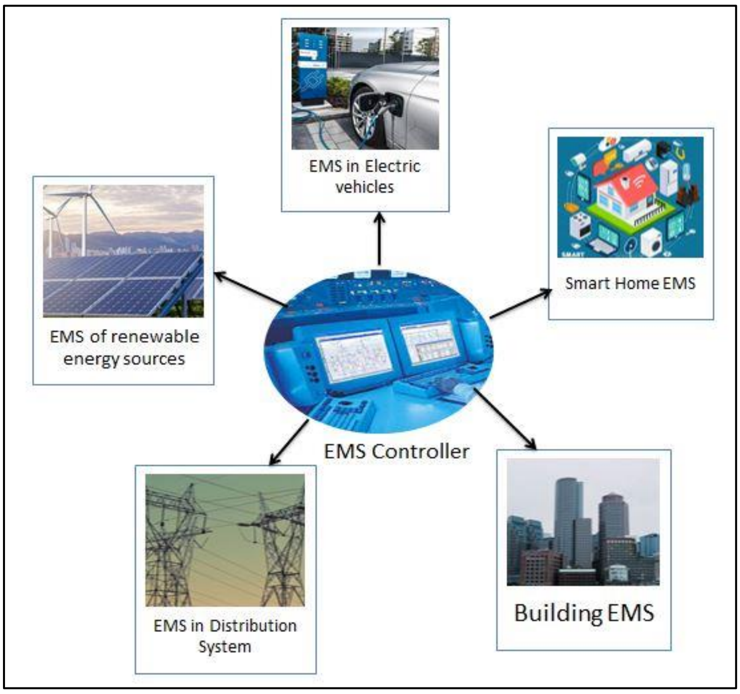

Fig. 2.1 Various Aspects of EMS

2.1 Smart Home Energy Management System

Households play a significant role in increasing energy demand. One-third of the total energy mandate comes from the residential segment. The main idea behind smart homes was to design an environment where everything including generation and storage is decided, monitored and controlled automatically with little or zero human interference. Using Home Area Network, every digital device is interlinked with each other and can be remotely controlled making it easier and economical for user. A lot of progress is already been made towards SHEMS. It is a demand response tool that shifts and curtails demand to perk up the energy consumption and production profile of a house or building according to electricity price and consumer comfort. The HEMS can communicate with household devices and the utility, as needed, and receive external information to improve the energy consumption and production schedule of household devices [13]. Fig. 2.2 shows the visualization of SHEMS. Loads in homes are categorized into controllable/scheduled loads and uncontrollable/unscheduled loads. SHEMS makes use of controllable loads such as washing machines, refrigerators, air conditioners etc. such that appliance scheduling can be done and optimization of energy can be implemented. Inclusion of renewable energy resources with EMS has opened way for new prospects towards eco-friendly environment.

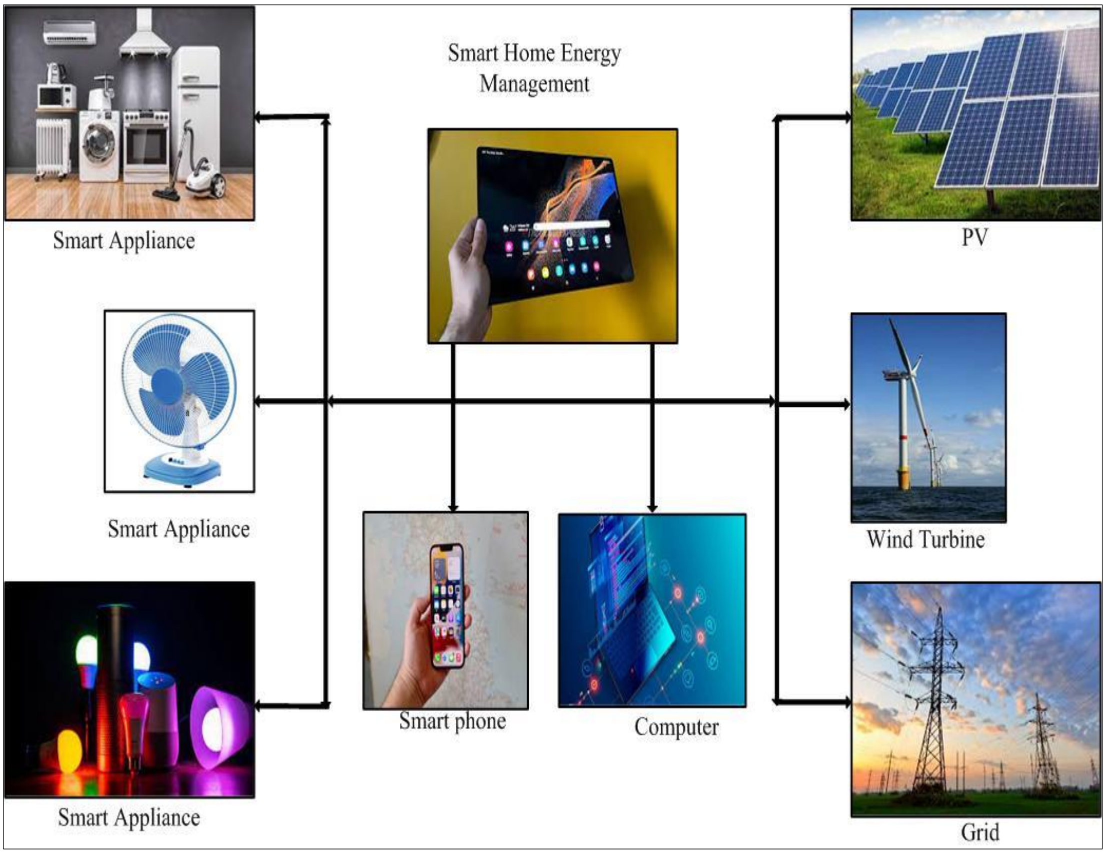

Fig. 2.2 Smart Home Energy Management System

In [14] a multi-objective mixed integer nonlinear programming (MO-MINLP) model is being discussed which aims at optimally using energy and at the same time taking care of user's comfort level in thermal and electric zones. It also deals with scheduling various loads according to a definite algorithm in order to save power. Under different user constrictions, the simulation results could provide successful reduction in energy use and optimal task scheduling. Another such work is presented in latest study [15] in which ICT is used to introduce an Automatic Home Management System. The two main algorithms used in the system are Power Limit Management (PLM) and Smart Electrical Task

Scheduling (SETS). PLM takes care of overloading and SETS having heuristic approach handles scheduling of loads. The software part of the system is implemented on IoT platform using Message Queuing Telemetry Transport (MQTT) protocol that transferences messages between various devices. The benefits of the system are also discussed using a case study of Gaza Strip which has restricted power sources.

Some important network protocols of Smart Homes include Zigbee, Z-wave, Thread, Bluetooth Mesh and Wi-Fi. One of the concerning factor in homes is consumption of unnecessary power by some appliances such as standby power. In [16] a Zigbee communication module is used to design a wireless power strip constructing a low cost and low power network based on IEEE 802.15.4 standard in order to reduce this standby power and the results have shown substantial decline in power consumption. The literature in [17] describes the effective switching of loads between renewable sources and grid energy using Artificial Neural Network and Machine Learning Algorithm, Support Vector Machine (SVM) thereby concluding superiority of SVM over ANN. These studies reveal that EMS together with Artificial Intelligence can provide wonderful solutions to optimize energy and household loads can be smartly managed using SHEMS.

2.2 Building Energy Management System

EMS has touched almost all the sectors including industrial, residential and academic. Building's energy consumption is a matter of great concern and hence managing it efficiently is the need of the hour. BEMS architecture mainly consists of communication system, interfacing technology and sensing technology. Several environmental factors like temperature, humidity, air quality, luminance etc. play a significant role in design of an effective BEMS which can manage almost all the considerations of building like heating, cooling, ventilation, security, alarm systems and all such. In [18], an efficient air conditioning system is designed that operates based on the occupancy of the building and is cost-effective too. It automatically adjusts the number of air conditioner units that are required to be operated at a time sensing the presence of people. Results say that it can save up to 22% of electricity bill. Similarly in [19] an EMS is designed for smart meters in residential building using fuzzy logic and implemented on microcontroller MSP430G2553. It saved energy consumption of the day by 7% and peak demand was reduced by 34%.

In June 2011, ISO 50001 standard was created by International Organization for

Standardization (ISO) that postulates the requirements for instigating an EMS in any type of organization irrespective of its size, segment or topographical location. The ultimate aim is to reduce electricity bills, save energy and control greenhouse effect. [20] Presents a detailed study of various aspects of ISO 50001 implementation and required tools for energy management.

2.3 Advanced Metering Interface

AMI forms the basis of EMS architecture and mainstay of Smart Grid. AMI is further made up of Smart Meters, Communication Network, Meter Data Acquisition System and Gateways. The electro-mechanical meters or manual electric meters have been in existence since long time now but owing to their major disadvantages like collecting data door to door which may be erroneous or unidirectional communication, emphasis is now shifted to Smart Energy Meters (SEMs). SEMs provide an interactive interface, self-healing or erroneous data and are multi-functional. They operate in a real-time environment and facilitate two way communications between energy providers and consumers [21].

Table 2.1 Electro-mechanical vs. smart meters

Conventional Meters/ Electro-Mechanical Meters	**Smart Energy Meters**
Basic and time-tested meters	Interactive and multifunctional
Manual data collection	Everything is digitally controlled
One-way communication from utility to consumers	Two-way communication between utility and consumers
Cannot provide energy efficiency	Can be effectively used for energy efficiency
Zero consumer participation	Very high consumer participation
Low accuracy	Highly accurate

AMI allows remote-control of meter data and thus any customized change during peak loading hours or off-peak loading hours can be done in order to save energy and power. In [22] a system is designed using KEIL software used to write an 8051 microcontroller program that merges GSM with AMI. It basically alarms users when their pre-paid balance for meters is too low and thus overloading of appliances can be controlled. Another interesting work is presented in [23]. In this a numerical optimization technique, Differential Evolution Algorithm is used for automatic load scheduling in SEM and simulation was implemented on MATLAB platform which ultimately minimizes energy consumption. A test site in New Delhi was selected for the purpose and the results showed that approximately 19.42% power was saved using DE Algorithm.

The robust communication protocol used in AMI is mainly described by three networks, Wide Area Network (WAN), Neighborhood Area Network (NAN) and Home Area Network (HAN) as shown in Fig. 2.3. These networks allow communication among digital devices within a home or neighborhood. Meter Data Acquisition System performs periodic evaluation of data collected from SEMs and accordingly logics are defined to sterilize the data.

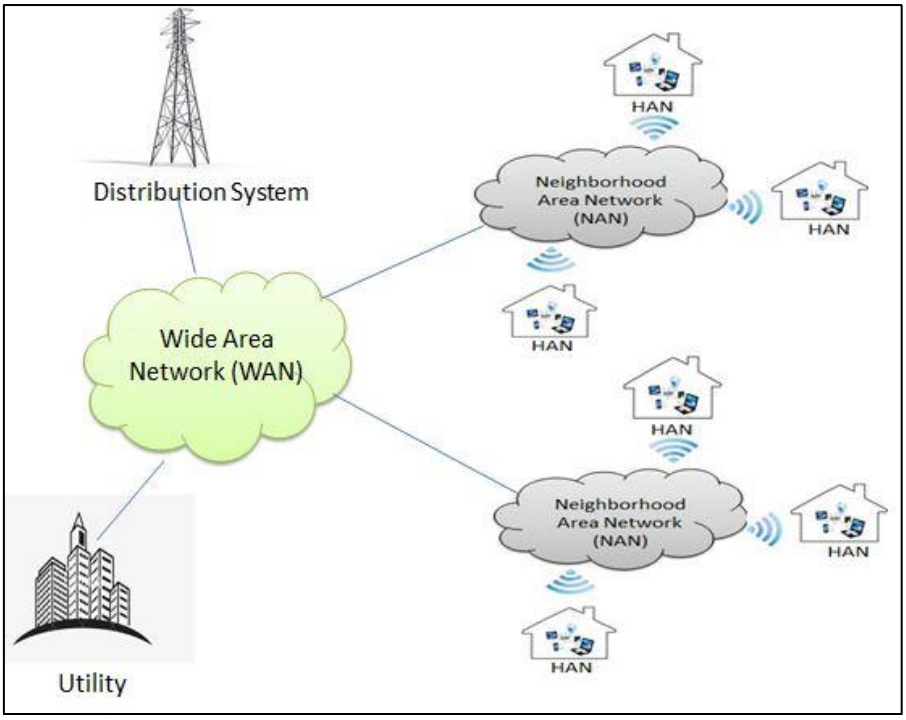

Fig. 2.3 Communication Protocol in AMI

More efforts should be aimed at creating regional or local energy hubs for centrally collaborating energy carriers and analyzing load curves of residential or industrial sectors for optimum energy saving.

2.4 EMS in electric vehicles

Introduction of EVs in smart grid has not only controlled pollution but also plays a significant role in power system optimization with their two ways operation i.e., Vehicle to Grid (V2G) in which they supply power to grid and Grid to Vehicle (G2V) in which power is supplied by the grid. Studies reveal that with the use of EVs, CO2 and NOX emission will be reduced [24]. Several studies have been done to analyze the impact of EVs charging and discharging in distribution system. Strong control strategies for EV charging stations reducing load burden on main grid is presented in [25]. A strong control is required in EVs which is achieved using EMS. [26] Describes the control strategies for diverse power sources used in hybrid electric vehicles. BEMS can help reduce electricity demands from residential and industrial sectors during peak loading hours and this energy can be used to charge EVs thus maintaining a balance between generation and consumption and simultaneously improving power quality.

2.5 Demand Side Energy Management System

Owing to two-way communication in SG, DSM allows users to enthusiastically participate in energy saving and conserving renewables by monitoring and altering their power consumption plans according to the dynamics. This is also called Demand Response Program (DRP). Residential DRP is classified into incentive based and price based DRP and the detail is given in [27].

Deep Learning has become one of the popular methods for forecasting and solving complex problems with great ease. One such model depicting the overall behavior of demand response is presented in [28]. A multi-level deep learning model with multi-stage ensemble has been proposed for power forecasting at appliance level and the performance of the algorithm is assessed on GREEND and UK-DALE, datasets that are openly obtainable. The presented model is robust, accurate and assures proper implementation of demand response programs.

Also in a country like India which is dominated by small sized and medium sized buildings, Building Energy Management Open Source Software (BEMOSS) is a platform that supports implementation of DR [29][30]. Since it is an open source platform it can be implemented via multiple protocols. It has also facilitated integration of IoT devices to monitor and regulate the data and simultaneously check energy consumption. Ultimately, DRP is encouraging consumers to become prosumers and increases reliability of grid.

2.6 Challenges in the way of EMS

Although implementation of EMS in distribution system has numerous benefits, however, there are some limitations that have to be taken care of in future designs. Some of the challenges identified and anticipated solutions are listed below.

Privacy issues are of utmost concern [31]. Large data collection may result in power thefts and cyber-attacks which are a frequent problem in AMI. More enhanced developments like advanced algorithms for cryptography are needed to maintain the security aspect of EMS. Literature in [32] presents a detailed analysis of energy savings algorithms implemented so far which can further be increased considering real time scenarios and developing prediction based models. Another challenge faced is maintenance. EMS is composed of sensing and controlling technologies that require frequent updating and maintenance in order to check system's performance which becomes a tedious task. Several complex architectures of EMS make it difficult for user to implement. More simplified designs are expected in future with the use of artificial intelligence.

The major challenge that comes for DRPs is the establishment of appropriate control strategies and reliable market frameworks for its optimal implementation. It is suggested to consider aggregated demands from various sources in order to form a novel modeling approach. Also, at times acquiring and monitoring data may be expensive which further restricts the fulfillment of the purpose of EMS. For this, use of distributed energy resources is a resilient way out. They are cost-effective and simultaneously meet sustainability goals.

It is expected that the future works in the field of Energy Management System would consider these challenges and a more socio-economic and techno-economic developments can be seen.

2.7 Conclusion

A thorough literature review is presented in this chapter in the relevant area for the present work "Particle Swarm Optimization and Differential Evolution Algorithm for Energy Management" in detail. Literature review is carried out to apprehend the scope of each algorithm and to understand each technique for the purpose of energy management.

CHAPTER 3
WORKING OF PSO AND DE ALGORITHMS

3.1 Particle Swarm Optimization Overview

Particle Swarm Optimization was first recognized by James Kennedy and Russell C. Eberhart in the year 1995 [33]. It is swarm intelligence centered stochastic algorithm employed to deduce the finest solution i.e. the minimum or maximum value in the multi-dimensional solution space [34]. It is differentiated from other algorithms as it can search very large solution space and makes negligible assumptions about the optimization problem. The hyper parameters required in PSO are also less as compared to other optimization algorithms. Ever since its introduction, researchers are continuously modifying PSO and numerous literatures describe its implementation in diverse problems. The visual explanation of particle swarm optimization is shown in Fig. 3.1.

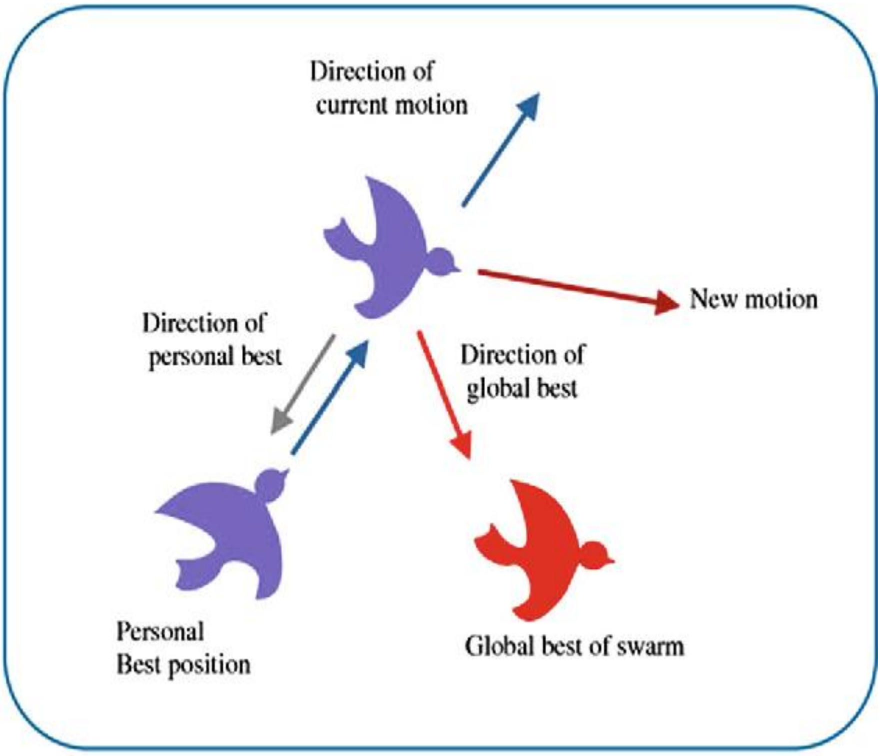

Fig. 3.1 Visual description of PSO

Paper [35] deals with use of PSO in devising a loss minimization technique during active power transmission whereas the simulation presented in [36] describes application of PSO in scheduling of EVs with micro-grid and its optimal management and results quite manifestly show the proficiency of PSO in resolving even the com-pound optimization functions. Many studies have also been conducted for choosing the correct value of hyper parameters used in PSO for obtaining most accurate and quick convergence of the algorithm [37].

3.2 Working of PSO

PSO is best used for obtaining maximum or minimum value of a function. A large search space called population is randomly generated and each particle in population is assigned a position. Besides the position, we also have a velocity for each particle at any iteration. At the next iteration, the position of each particle would be restructured or updated as and at the same time, the velocities are also updated by specified rule. The parameter **ω** is called the inertia weight constant whose value lies between 0 and 1 and determines how much velocity the particle should match with its previous velocity (i.e., speed and direction of the exploration). The parameters **α1** and **α2** are called the cognitive coefficient and the social coefficients of PSO respectively. They have power over how much weight should be given between refining the search product of the particle itself and recognizing the search result of the entire swarm [34]. The appropriate selection of values for all the hyper parameters in PSO plays a major role in working of the algorithms. We can consider that these parameters control the tradeoff between exploration and exploitation.

One attention-grabbing property of PSO algorithm that distinguishes it from other popular optimization algorithms is that it does not depend on the gradient or slope of the objective function. For any particle at any location at any instant, how it moves does not depend on which direction is the “down hill” but only on where are pbest and gbest positions is. This makes PSO particularly suitable if differentiating a function is at all difficult. Another remarkable property of PSO is that it can be parallelized quite easily. As we are manipulating multiple particles to find the optimal solution, each particle can be updated in parallel and we only need to pull together the updated value of gbest once per iteration [34]. This makes trouble-free architecture a perfect entrant to implement PSO.

The flowchart of PSO describing the steps followed for optimizing an objective function is shown in Fig. 3.2 below-

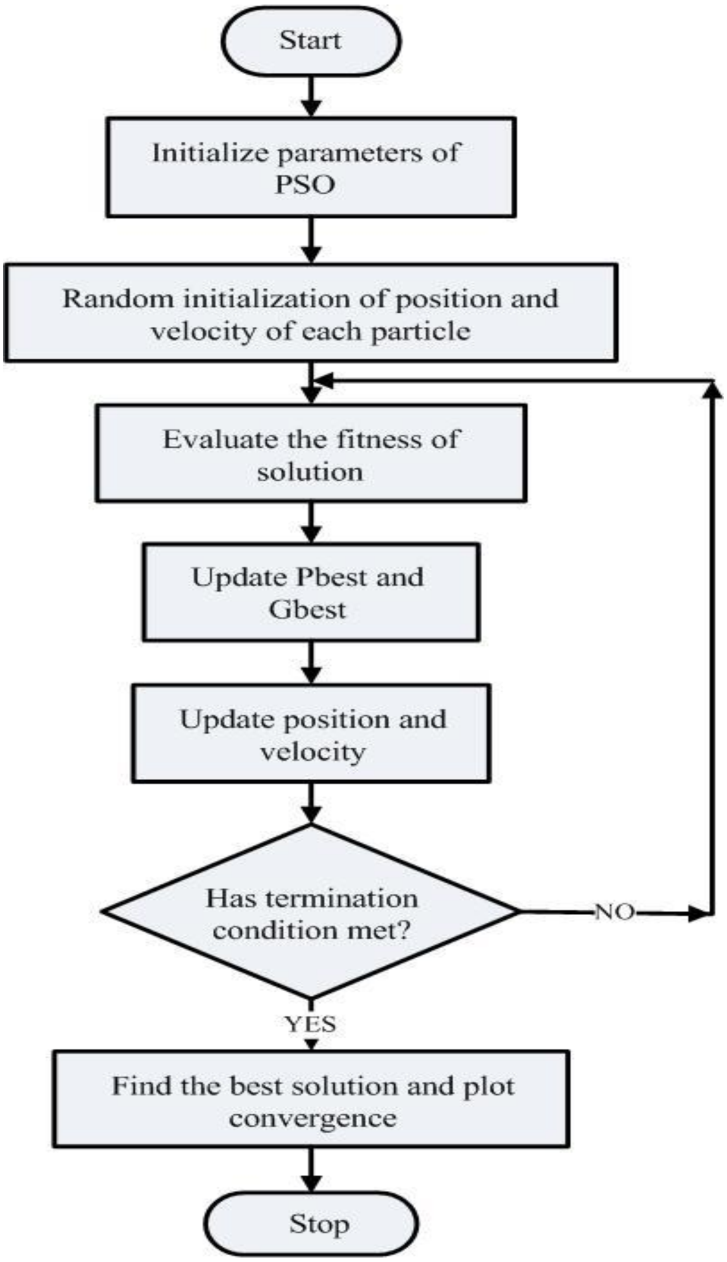

Fig. 3.2 Flowchart of PSO

3.3 Problem Definition

The objective function representing the consumption of power which is to be minimized using PSO and DE remains same and is defined as-

$$Obj = \sum_{i=1}^{Np} P(i) \tag{3.1}$$

Where *Obj* is the objective function, *Np* is the size of population and *P(i)* is the power consumption equation represented in terms of decision variables as-

$$P(i) = \sqrt{3} V_i I_i (\cos\phi)_i$$

(3.2)

Where V_i represents the parameter of line voltage, I_i represents parameter for line current and $(cos\phi)_i$ is parameter for power factor. Considering the constraints defined for the problem, the final expression becomes-

$$P(i) = \sqrt{3}V_i I_i (\cos\phi)_i [1-\lambda]$$

(3.3)

λ is the coefficient for constraint violation whose value is either 0 or 1 as per defined rules.

3.4 Mathematical Modeling of PSO

PSO starts with definition of the problem and then arbitrary initialization of the population and each solution in PSO is referred to as a particle. Three distinct features of PSO are $P_{best,i}$ which is the best solution achieved by i^{th} particle, best fitness achieved by any particle in the population known as G_{best} and velocity and position update of each particle to discover the search space for optimal solution.

3.4.1 Position and Velocity Update: Position of any particle i is updated as-

$$x_i^{(n+1)} = x_i^{(n)} + v_i^{(n+1)} \tag{3.4}$$

Where n denotes the generation number, Np is the population size, $x_i^{(n+1)}$ is the updated position, $x_i^{(n)}$ denotes the current position and $v_i^{(n+1)}$ is the updated velocity of particle i which is given as-

$$v_i^{(n+1)} = \omega v_i^{(n)} + \alpha_1 r_1 (P_{(i,lb)}^{(n)} - x_i^{(n)}) + \alpha_2 r_2 (P_{gb}^{(n)} - x_i^{(n)}) \tag{3.5}$$

In the above equation, ω represents the inertia of the particle which is user-specified, α_1 and α_2 are called the acceleration coefficients which are also user-specified and r_1 and r_2 are random numbers ∈ [0, 1]. $P_{(i,lb)}$ is the local best of i^{th} particle and P_{gb} is the global best. The velocity equation has three components-

- The momentum part, $\omega v_i^{(n)}$ which stores the memory of flight direction and is also called inertia component.
- The cognitive part, $\alpha_1 r_1 (P_{(i,lb)}^{(n)} - x_i^{(n)})$ which stores the previous best position and quantifies performance of the algorithm.

- The social part, $\alpha_2 r_2(P_{gb}^{(n)} - x_i^{(n)})$ which stores the global best of particles and changes position based on the best fitness of the population.

3.4.2 Pbest and Gbest Positions: Once the position and velocity of a particle gets updated, its local best and global best position is evaluated. So, here the local best of the particle is updated to the new position of the particle if the fitness at new position is smaller than the local best found so far otherwise the same local best is kept without any updating. The expression for local best is given as-

$$P_{(i,lb)}^{(n+1)} = \begin{cases} x_i^{(n+1)} & if \quad f(x_i^{(n+1)}) < f(P_{(i,lb)}^{(n)}) \\ P_{(i,\mathrm{lb})}^{(\mathrm{n})} & \text{otherwise} \end{cases} \tag{3.6}$$

And the global best solution of the particle belongs to one of the local best such that the fitness value of the global best of entire population is the lowest amongst all the solutions and can be expressed as-

$$P_{gb}^{(n)} \in \{x_1^{(n)},......,x_{\mathrm{Np}}^{(\mathrm{n})}\} \mid \mathrm{f}(\mathrm{P}_{\mathrm{gb}}^{(\mathrm{n})}) = \min\{\mathrm{f}(x_1^{(\mathrm{n})}),...,\mathrm{f}(x_{\mathrm{Np}}^{(\mathrm{n})})\} \tag{3.7}$$

3.5 Differential Evolution Algorithm Overview

Differential Evolution is another meta-heuristic algorithm that was introduced in 1990s by Storn and Price and since then it has been majorly used by researchers in optimizing various problems [38]. DE and its modified or hybrid form is used to solve power flow problem in micro grids [39], automated load scheduling and complex functions with high dimensionality [40]. Just like PSO, DE is also stochastic population based technique wherein every element called genome or chromosome iteratively undergoes three stages called mutation, recombination and finally the selection of most suitable solution is done.

3.6 Working of DE

DE is another most admired optimization method used for optimizing multidimensional real-valued functions which makes use of a random population of individual solutions. This method just like PSO algorithm does not involve gradient information of any function, which means that the problem to be optimized does not have to be differentiable as other classical optimization methods require. It can be applicable even to problems that are not continuous. The algorithm searches the available design space or search space by maintaining a population of candidate solutions (individuals) and forming new solutions by combination of existing solutions according to a specific defined process of mutation, crossover and selection. The candidates or the solutions having the best objective values are retained in the next iteration of the algorithm in a scheme that the new objective value obtained of an individual is enhanced as compared to previous values designated; otherwise the new obtained objective value is discarded from the process. The procedure repeats itself until a given termination criterion is satisfied.

The choice of DE parameters **Np** (population size) , **C_R** (crossover rate) and ***f*** (differential weight) does have a large impact on the performance of optimization algorithm. Selecting the fitting DE parameters that yield good performance has therefore been an important subject matter of research. The flowchart of differential evolution algorithm is shown below in Fig. 3.3

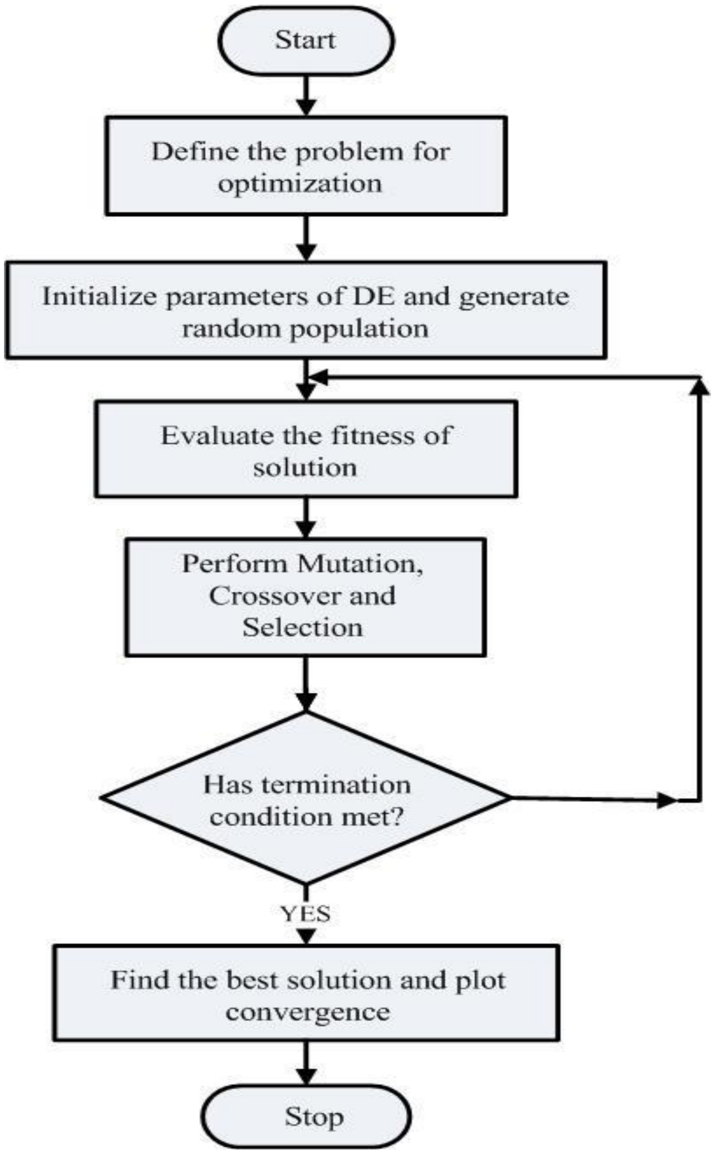

Fig. 3.3 Flowchart of DE Algorithm

3. 7 Mathematical Modeling of DE

Once the problem formulation is done and objective function is defined, DE starts with initializing all the parameters and randomly generating a population of size Np where each member goes through a cycle of mutation, crossover and selection of the fittest. Each of the phases is described below-

3.7.1 Mutation: Mutation in DE is the process of forming a new vector by combining three random vectors from the population defined as-

$$x_i^{n+1} = x_a^n + f(x_b^n - x_c^n) \tag{3.8}$$

Where x_i is the mutant vector, x_a, x_b and x_c are randomly selected vectors from the population and f is the scaling factor or differential weight [0,1] for speedy convergence.

3.7.2 Crossover: Process of creating new generation by binomially distributing present vector and new vector is called crossover. It is expressed as-

$$\hat{x}_i^{n+1} = \begin{cases} x_{ji}^{n} & if \ random\ no. > C_R \\ x_{ji}^{n+1} & otherwise \end{cases} \tag{3.9}$$

C_R is the crossover rate [0, 1] which is assigned by user.

3.7.3 Selection: In DE, greedy selection is applied to select the fittest vector out of all the solutions. For each solution, a donor vector and a trial vector is generated and greedy selection is performed between the two to select the fittest of the two.

3.8 Conclusion

This chapter presented a detailed description of both the algorithms used for implementing energy management, their mathematical modeling and working. The problem statement that is being optimized is also described and the further results and detailed discussion is given in next chapter.

CHAPTER 4
EXECUTION OF PSO AND DE FOR ENERGY MANAGEMENT

4.1 Methodology of Work

In this work, the main objective is to implement energy management system in a building or a workplace. For this purpose, two popular machine learning algorithms are selected and implemented in order to curtail power consumption in buildings or households and a comparative study is performed between the two to discuss the superiority of one over the other considering various performance parameters. Algorithms are modeled in such a way as to bound power consumption within certain limits. This is an analytical approach wherein the data from smart energy meter present in UEE Laboratory in Delhi Technological University, Delhi, India is taken for testing the algorithms. The SEM utilizes the data from a local PV source present at the test site and is further connected to automated data loggers. The entire laboratory setup is shown in Fig. 4.1. The data obtained is of 15 days starting from middle of December to January, 2020. This data consists of per hour values of three phase voltages, three phase currents, power factor, temperature, irradiance value, total harmonic distortions and power consumption of laboratory.

While modeling the algorithms, three decision variables are taken viz. voltage, current and power factor. The definition of problem or the objective function is the three phase power consumption equation having voltage current and power factor parameters. The limit of voltage is set between 220 to 230V, current limit is set to 1.18 to 1.23A and power factor range is set between 0.90 to 0.93. These limits (upper bounds and lower bounds) are decided on the basis of meter data. The data had per hour values of all parameters. The power consumption limit is set to not exceed more than 460 Watts during the day. If the desired solutions are within the range then algorithm runs and gives the optimized results and if at any iteration, the limits are violated the desired results becomes zero.

This is the analytical process which when tested with all the desired conditions and constraint limits gave satisfactory results.

Fig. 4.1 Laboratory setup of Smart Energy Meter

When these algorithms will be integrated with SEM, we can easily achieve automated load scheduling. As the consumption will increase the desired set range, appliances can be turned off based on the defined priority for appliance scheduling and consecutively we can get a significant reduction in energy consumption and reduced electricity bills. In real-time scenario to productively achieve this goal the EM should slip in a colossal assortment of resources like different types of storage units and distributed generation system. This setup will be beneficial to both electricity consumers and suppliers and is a great step towards energy management.

The entire work done in this dissertation is summarized in the form of a flowchart as shown in Fig. 4.2.

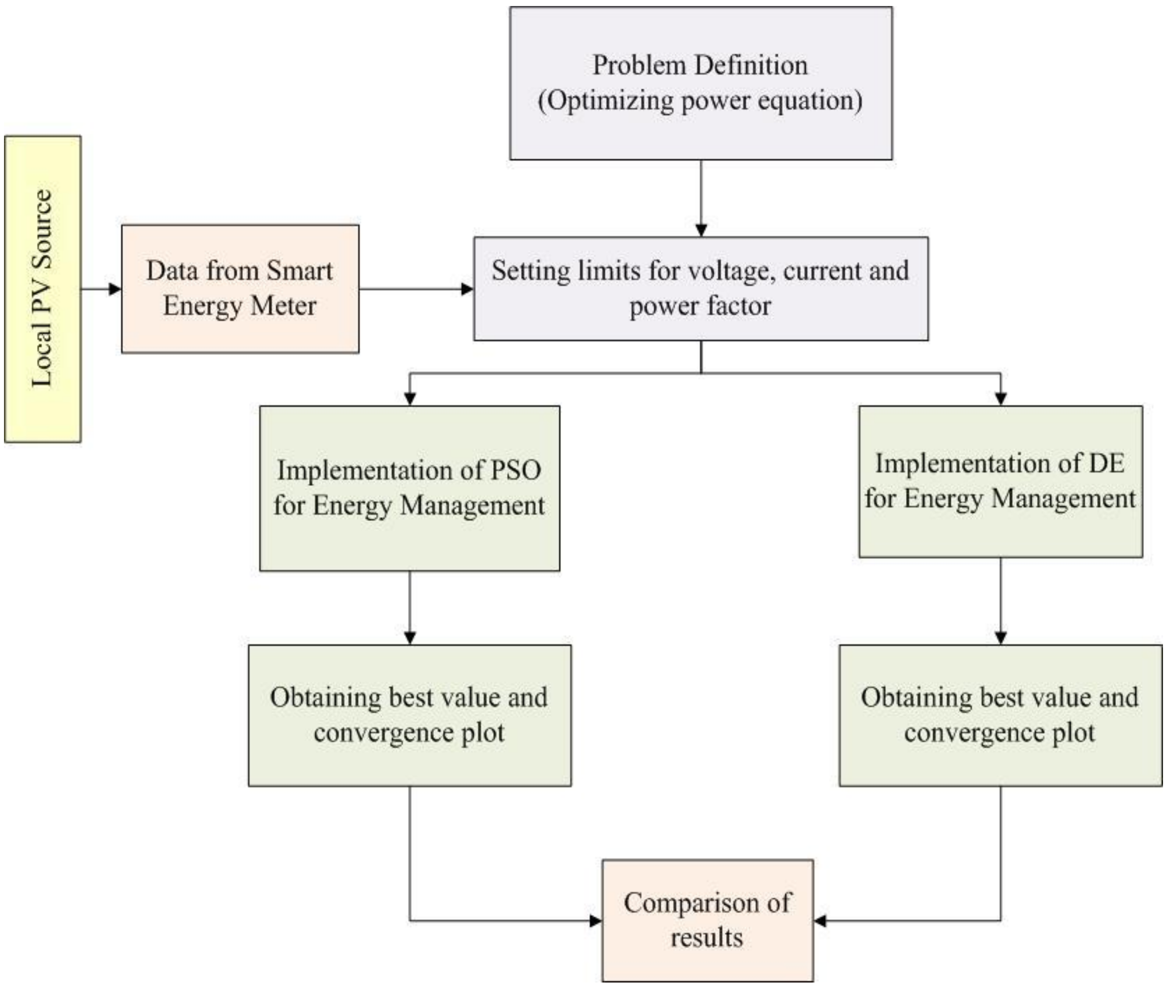

Fig. 4.2 Methodology of the work presented

4.2 Data from Smart Energy Meter

The constraints for the algorithms are defined using the data obtained from smart energy meter present in Utilization of Electrical Energy (UEE) Laboratory in Delhi Technological University, Delhi, India. The three phase voltage, current and power consumption data of UEE laboratory is shown in figures below

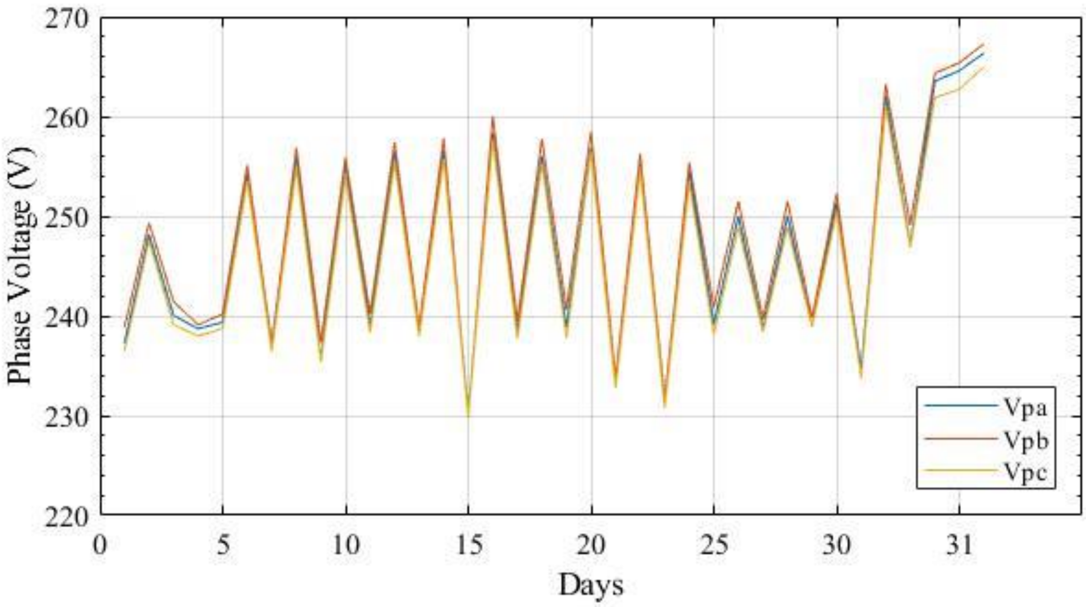

Fig. 4.3 Three Phase Voltage Data obtained from SEM

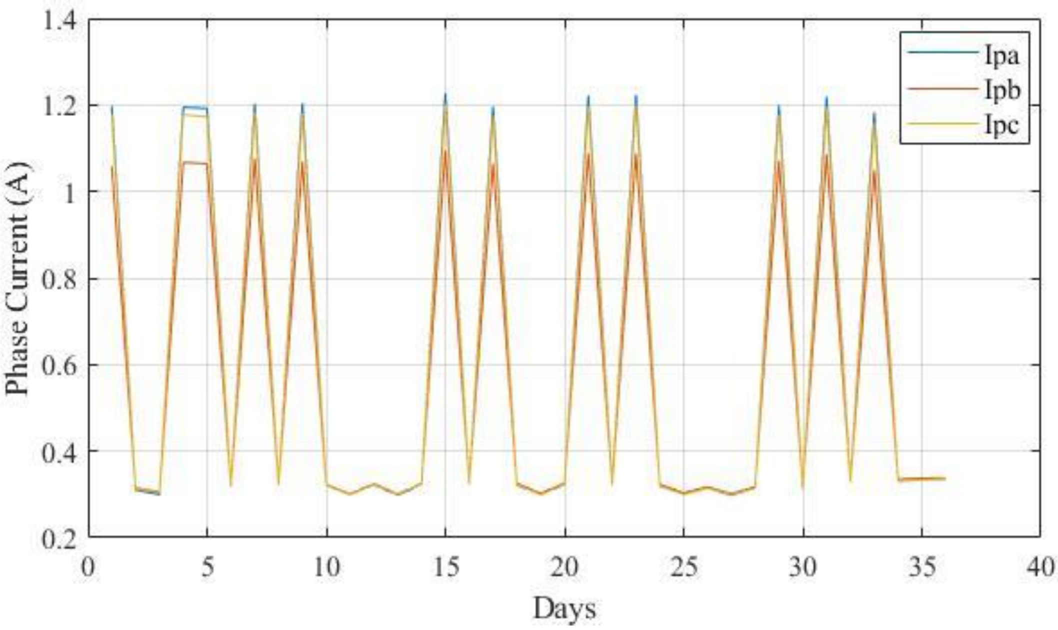

Fig. 4.4 Three phase current data obtained from SEM

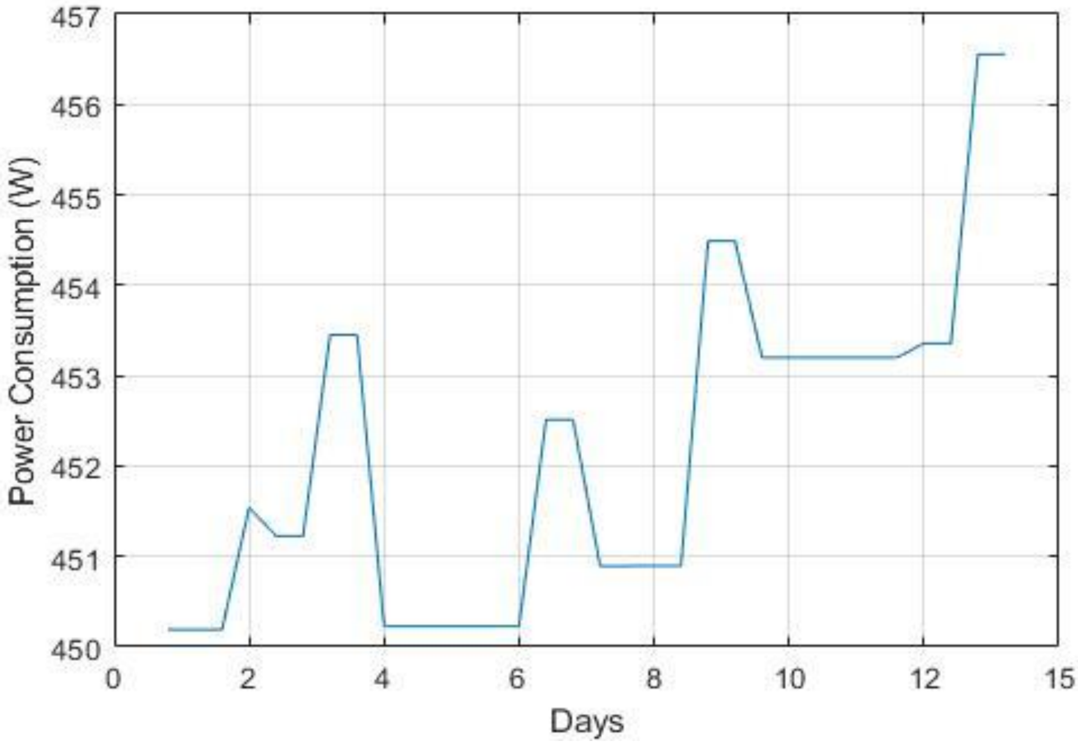

Fig. 4.5 Power consumption data of 15 days

Fig. 4.3, Fig. 4.4 and Fig. 4.5 show the voltage of three phases, currents of each phase and actual power consumption respectively of the lab for 15 days. Table 4.1 gives the value of data obtained from SEM. This real-time data is used to define the limits for voltage, current and power factor to curtail power consumption within desired range and test the efficiency of the algorithms.

Table 4.1 Data from SEM

Date	**Time**	**Radiation**	**Voltage**	**Frequency**	**Current**	**Power Factor**	**Power Consumed**
16-12	11:20	207	237.273	49.975	1.197	0.914	450.189
16-12	23:00	0	248.180	50.03	0.310	0.003	0.387
17-12	09:00	147	238.720	50.082	1.194	0.914	451.539
17-12	22:00	0	240.041	49.997	0.299	0.002	0.254
18-12	10:00	450	239.365	49.867	1.192	0.913	451.226
18-12	23:00	0	254.221	50.013	0.318	0.002	0.3948

19-12	10:00	308	237.326	50.026	1.203	0.916	453.452
19-12	23:00	0	256.112	50.077	0.321	0.001	0.255
20-12	10:00	315	235.608	49.982	1.204	0.916	450.227
20-12	23:00	0	254.456	49.977	0.320	0.001	0.277
23-12	10:00	211	230.306	49.886	1.227	0.924	452.514
23-12	23:00	0	258.329	49.978	0.299	0.002	0.292
24-12	11:00	374	238.507	49.996	1.196	0.912	450.894
24-12	23:00	0	256.032	50.017	0.323	0.003	0.333
26-12	10:00	216	233.104	49.980	1.221	0.921	454.490
26-12	23:00	0	256.001	49.999	0.325	0.001	0.130
27-12	10:00	383	231.685	49.984	1.223	0.923	453.200
27-12	23:00	0	254.529	49.991	0.319	0.002	0.191
30-12	10:00	117	238.895	50.047	1.198	0.914	453.358
30-12	23:00	0	240.664	49.993	0.313	0.003	0.161
31-12	09:00	220	234.622	49.779	1.219	0.921	456.553
31-12	23:00	0	250.452	50.019	0.329	0.005	0.083
01-01	10:00	275	247.102	49.911	1.183	0.904	457.814
01-01	23:00	0	249.56	50.069	0.313	0.003	0.618

4.3 Optimization results of PSO

The PSO algorithm was successfully modeled on MATLAB platform (version 2017) and is tested using the real-time data obtained from SEM. It was run with multiple parameter settings and each time the optimization plot was observed and compared with other values. Swarm size or population size greatly affects the performance of PSO. Less population may lead to pre-mature convergence and a large swarm size can slow down the convergence and therefore it is a requisite to find the perfect balance of population size in PSO. Various parameter settings, convergence time and best value of convergence obtained are shown in Table 4.2.

Table 4.2 Various parameter settings of PSO

Population/ Swarm Size	**Number of Iterations**	**Inertia weight (ω)**	**Cognitive Co-efficient (α1)**	**Social Co-efficient (α2)**	**Best Value (Watts)**
150	200	0.5	0.5	0.5	417.36
150	100	0.8	1	1	417.36
150	50	1	2	2	414.52
100	200	0.5	0.5	0.5	414.52
100	100	0.8	1	1	414.52
100	50	1	2	2	413.07
50	200	0.5	0.5	0.5	409.44
50	100	0.8	1	1	409.44
50	50	1	2	2	404.70

After running the algorithm with multiple parameter settings, it was observed that most optimal results were obtained at **ω= 1, α1=2** and **α2=2** with the population size taken as **50**.

The convergence time of the algorithm was less than 15 seconds and the final optimized value of power came out to be 404.7 W. Considering this optimized value and comparing with the highest value of power obtained from SEM, approximately 11.5% of reduction in power can be achieved making PSO as one of the most efficient algorithm for power optimization. Fig. 4.4 shows the convergence plot of PSO run with optimal parameter settings.

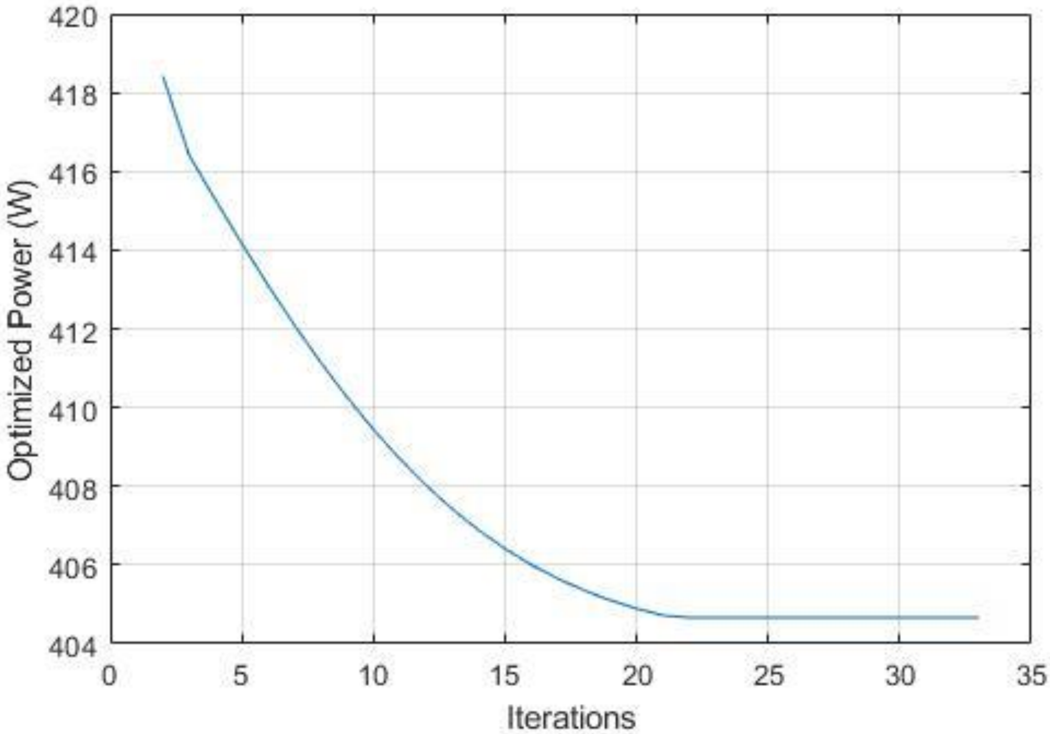

Fig. 4.6 Convergence plot of PSO

4.4 Optimization results of DE algorithm

The Differential Evolution Algorithm was successfully modeled and run on MATLAB platform (version 2017). The performance of the algorithm heavily depends on the parameter settings. There are three strategy parameters in DE, the population size Np, the crossover rate C_R and the scaling factor *f*. Several works have been done to study the suitable setting of these control parameters. The C_R parameter is responsible for the influence of the parent in the generation of the off-spring. The *f* parameter scales the influence of the set of pairs of solutions chosen to calculate the mutation value [40]. DE performs the perturbation based on the division of the solutions in the current population. In this way, search directions and probable step sizes depend on the location of the individuals chosen to calculate the mutation values. Also, there are several variants of mutation in DE. The present work made use of rand/1/bin method. Selecting the appropriate mutation strategy also largely affects the convergence of the algorithm.

The algorithm was run with multiple parameter settings and each time the optimization plot was observed. Various parameter settings, convergence time and best value of convergence obtained are shown in Table 4.3.

Table 4.3 Various parameter settings of DE

Population Size	Number of Iterations	Differential weight (*f*)	Crossover Probability (C_R)	Best Value (Watts)
150	200	0.5	0.2	419.26
150	100	0.8	0.5	419.26
150	50	1	0.8	419.26
100	200	0.5	0.2	419.26
100	100	0.8	0.5	419.26
100	50	1	0.8	418.54
50	200	0.5	0.2	418.54
50	100	0.8	0.5	418.54
50	50	1	0.8	417.37

After running the algorithm with multiple parameter settings, it was observed that most optimal results were obtained at ***f=1*** and ***C_R =0.8*** for a population size taken as **50**. The convergence time of the algorithm was less than 15 seconds and the final optimized value of power came out to be 417.37 W. Considering this optimized value and comparing with the highest value of power obtained from SEM, approximately 9.4% of reduction in power can be achieved in the best case scenario making DE an efficient algorithm. But comparing the results of both DE and PSO, it is seen that PSO is superior to DE. So, overall both the algorithms can result in saving power but in present work PSO supersedes DE algorithm by providing highly efficient results. Fig. 4.5 shows the convergence plot of DE algorithm run with optimal parameter settings.

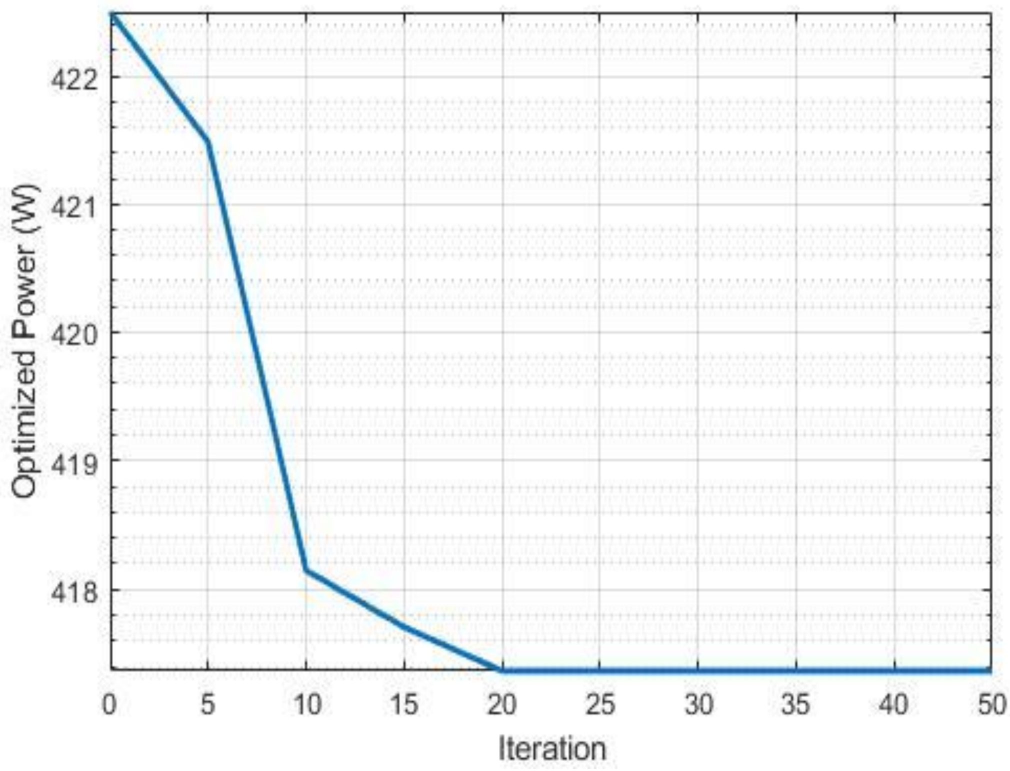

Fig. 4.7 Convergence plot of DE

4.5 Comparison of PSO and DE

With same problem definition and optimizing the same objective function, in the two implemented algorithms, PSO and DE, one of the key differences is in the mechanism to generate a new population of solutions via perturbation of solutions from the old population to the new population. These different mechanisms engender a population of solutions with diverse balance between amplification and diversification. This dynamic behavior of the population can be deducted from the fundamental perturbation method used in the creation of new solutions. The values shown in the graph clearly show that PSO converges to a lower value than DE with similar rate of convergence. For lower dimensions problem DE is suitable whereas PSO works well with higher dimensions as well. Also, PSO is simpler and easy to implement algorithm compared to DE as there are three different models in DE, mutation, crossover and selection.

So, overall both the algorithms can result in saving power but in present work PSO supersedes DE algorithm by providing highly efficient results. This arrangement is sound both financially and practically for electricity consumers and also producers as both total cost and energy both are saved. The reduced value of power consumption obtained through convergence can also minimize losses. Table 4.4 shows a comparative analysis between the two algorithms.

Table 4.4 Comparison of PSO and DE

Performance Parameters	**PSO**	**DE**
Optimal value of power	404.67 W	417.37 W
Power saving	11.5%	9.4%
Convergence speed	High	Comparatively High
High dimensionality problems	Suitable	Not suitable
Pre-mature convergence	Low	High

4.6 Conclusion

Thus, this chapter describes that the algorithms are tested using the historical data obtained from smart energy meter located in UEE Laboratory at Delhi Technological University, Delhi, India. The data gathered is over a period of 15 days starting from mid of December to January. The constraints for optimization is defined based on the range of voltage, current and power obtained from the meter data. Both the analytical methods were tested individually and then a comparative study was deduced wherein PSO saved approximately 11.5% power and DE resulted in 9.4% reduction of power.

CHAPTER 5
CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

As more and more researches are being done to improve the energy management system as applied to smart grid, this work provided a wide-ranging review of most recent stage of developments in this field. EMS implementation in different fields is presented to give readers an idea of its vast applications. Further the challenges that may be encountered are also presented and day by day extensive research and developments are already being done to make EMS more reliable and secure. Proper management and utilization of electricity is the most thought-provoking area which is averting the researchers and every day modern optimization techniques are evolving.

In the presented work, in order to curtail power consumption in buildings and households, a novel approach using PSO and DE algorithm was implemented. The modeling and simulation of algorithms based on Particle Swarm Optimization and Differential Evolution for the purpose of minimization of energy consumption is carried out on MATLAB platform (version 2017). The algorithms are tested using the historical data obtained from smart energy meter located in UEE Laboratory at Delhi Technological University, Delhi, India. The data gathered is over a period of 15 days starting from mid of December to January. The constraints for optimization is defined based on the range of voltage, current and power obtained from the meter data. Both the analytical methods were tested individually and then a comparative study was deduced wherein PSO saved approximately 11.5% power and DE resulted in 9.4% reduction of power. The comparison of convergence of PSO and DE is shown in Fig. 5.1.

PSO was found to be superior to DE although both are flexible algorithms that can integrate with different optimization techniques to develop a hybrid algorithm, PSO escapes from local minima. Also, PSO does not require a first-class initial solution to initiate the iteration process.

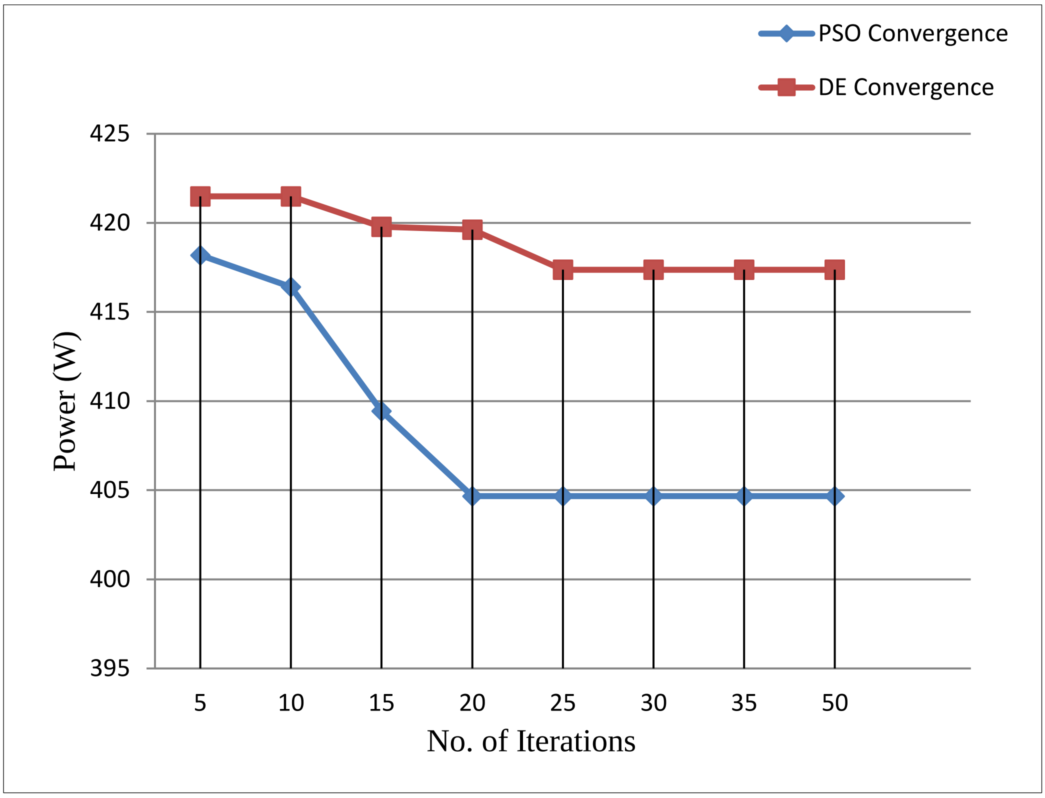

Fig. 5.1 Convergence comparison of PSO and DE

Both Particle Swarm Optimization and Differential Evolution algorithms can be used in number of applications like data mining, sensors and networks, power system applications like scheduling, monitoring and prediction, image and video analyzing and optimizing applications. Implementation in industrial scale controller can also be done.

5.2 Future Scope

- Future aspect of this work includes integrating these models with smart energy meter and operating in real-time. This could also lead to automated load scheduling of all the appliances and successively a remarkable reduction in electricity bills can be achieved making it economical and most sought after solution for consumers.
- Further modifications in the algorithm using combined approach of multiple other optimization techniques and making use of longer duration data is open for researchers which can yield even better results with little complexity.
- More efforts should be aimed at creating regional or local energy hubs for centrally collaborating energy carriers and analyzing load curves of residential or industrial

sectors for optimum energy saving.

- Merging more AI techniques with EMS is an area to be explored so that zero human interaction can be achieved with reduced complexity.
- Execution of Time of use (TOU) metering can be done. It is a trait in which utility firms charge the customers based on their energy consumption arrays during peak, off peak and mid peak hours. This would lessen the strain on the grid.

LIST OF PUBLICATIONS

On the grounds of work presented in this dissertation, three conference papers are written and presented in SCOPUS indexed conference as mentioned below:

[1] Amisha Srivastava, M. Rizwan, Rinchin W. Mosobi, "Energy Management System: A Review on Ruling and Reckoning Opportunities to Save Energy", 3rd International Conference on Machine Learning, Advances in Computing, Renewable Energy and Communication (MARC), Ghaziabad, UP, India on 10-11 December, 2021.

[2] Amisha Srivastava, M. Rizwan, Rinchin W. Mosobi, "Comparative Analysis of Particle Swarm Optimization and Differential Evolution Algorithm to Curtail Power Consumption using Smart Energy Meter Analytics", 2022 IEEE Second International Conference on Advances in Electrical, Computing, Communications and Sustainable Technologies (ICAECT 2022), Bhilai, Chattisgarh, India on 21-22 April, 2022.

[3] Srijan Singh, Amisha Srivastava, M. Rizwan, Astitva Kumar, “An Adaptive Intelligent Approach to Implement Energy Efficiency Concept in Built Infrastructure”, Third International Conference on Intelligent Computing, Instrumentation and Control Technologies, ICICICT 2022.

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APPENDIX-I
MATLAB CODE

- **Particle Swarm Optimization Code**

```
clc;
clear;
close all;

   %% Problem Description

   nVar = 3;                          % Number of Decision Variables
   VarMin = [220 1.18 0.90];          % Lower Limit of Decision Variables
   VarMax = [250 1.23 0.93];          % Upper Limit of Decision Variables

   %%Parameter Setting of PSO

   MaxIter = 50;                      % Maximum No. of Iterations
   nPop = 150;                        % Population Size or Swarm Size
   w = 1;                             % Inertia Coefficient
   wdamp = 0.99;                      % Damping Ratio of Inertia Coefficient
   c1 = 2;                            % Personal Acceleration Coefficient
   c2 = 2;                            % Social Acceleration Coefficient

   %% Initialization

   % The Particle Template
   a0.position = [];
   a0.velocity = [];
   a0.fitness = [];
   a0.best.position = [];
   a0.best.fitness = [];

   % Create Population Array
   a = repmat(a0, nPop, 1);

   % Initialize Global Best
   global_best.fitness = inf;

   % Initialize Population Members
   for i=1: nPop

      % Generate Random Solution
      for k = 1:nVar
```

```
        a(i).position(k) = unifrnd(VarMin(k), VarMax(k));
    end

    % Initialize Velocity
    a(i).velocity = zeros([1 nVar]);

    % Evaluation
    a(i).fitness = objective_function(a(i).position);

    % Update the Personal Best
    a(i).best.position = a(i).position;
    a(i).best.fitness =a(i).fitness;

    % Update Global Best
    if a(i).best.fitness < global_best.fitness
        global_best = a(i).best;
    end

end

% Array to Hold Best Cost Value on Each Iteration
B = zeros(MaxIter, 1);
C = zeros(MaxIter,nVar);


%% Main Loop of PSO

for j = 1:MaxIter

    for i=1:nPop

        % Update Velocity
        a(i).velocity = w*a(i).velocity + c1*rand([1 nVar]).*(a(i).best.position - a(i).position)
+ c2*rand([1 nVar]).*(global_best.position - a(i).position);

        % Update Position
        a(i).position = a(i).position + a(i).velocity;

        %check the range
        for k = 1:nVar
            if a(i).position(k) < VarMin(k)
                a(i).position(k) = VarMin(k);
            end
            if a(i).position(k) > VarMax(k)
```

```
            a(i).position(k) = VarMin(k);
          end

        end

      end
      a(i).fitness = objective_function(a(i).position);
      if a(i).fitness < a(i).best.fitness
        a(i).best.position = a(i).position;
        a(i).best.fitness =a(i).fitness;
        if a(i).best.fitness < global_best.fitness
          global_best = a(i).best;
        end
      end


      % Damping Inertia Coefficient
      w = w * wdamp;

      %save best fitness
      B(j)=global_best.fitness;
      C(j,:)=global_best.position;
      disp(['Iteration ' num2str(j) '; Best fitness = ' num2str(B(j)) '; Optimal solution (V, I, PF)
= ' num2str(C(j,:))]);
      plot(B(1:j,1),'linewidth', 2); drawnow
    end
```

- **Differential Evolution Algorithm**

```
clc;
clear;
close all;

%% Problem Description

nVar=3;                          % Number of Decision Variables

VarSize=[1 nVar];                % Decision Variables Matrix Size

VariaMin = [225 1.19 0.90];      % Lower Bound of Decision Variables
VariaMax = [230 1.24 0.92];      % Upper Bound of Decision Variables

%% DE Parameter Setting
```

```
MaxIt=50;                          % Maximum Number of Iterations

nPop=100;                          % Population Size

sc_min=0.4;                        % Lower Bound of Scaling Factor
sc_max=0.6;                        % Upper Bound of Scaling Factor

CR=0.2;                            % Crossover Probability

%% Initialization of DE

null_individual.Position=[];
null_individual.Val=[];

BestSol.Val=inf;

pop=repmat(null_individual,nPop,1);

for i=1:nPop

    pop(i).Position=unifrnd(VariaMin,VariaMax,VarSize);

    pop(i).Val=objective_function(pop(i).Position);

    if pop(i).Val<BestSol.Val
        BestSol=pop(i);
    end

end

BestVal=zeros(MaxIt,1);

%% DE Main Loop

for it=1:MaxIt

    for i=1:nPop

        x=pop(i).Position;

        D=randperm(nPop);

        D(D==i)=[];
```

```
    d=D(1);
    e=D(2);
    c=D(3);

    % Mutation

    %beta=unifrnd(sc_min,beta_max);
    beta=unifrnd(sc_min,beta_max,VarSize);
    y=pop(a).Position+beta.*(pop(b).Position-pop(c).Position);
    y = max(y, VariaMin);
    y = min(y, VariaMax);

    % Crossover

    z=zeros(size(x));
    y0=randi([1 numel(x)]);
    for y0=1:numel(x)
        if y==j0 || rand<=CR
            z(j0)=y(j0);
        else
            z(j0)=x(j0);
        end
    end

    NewSol.Position=z;
    NewSol.Val=objective_function(NewSol.Position);

    if NewSol.Val<pop(i).Val
        pop(i)=NewSol;

        if pop(i).Val<BestSol.Val
           BestSol=pop(i);
        end
    end

end

% Update Best Cost
BestVal(it)=BestSol.Val;

% Show Iteration Information
disp(['Iteration ' num2str(it) ': Best Val = ' num2str(BestVal(it))]);
```

```
end
```

%% Show Results

```
figure;
%plot(BestVal);
semilogy(BestVal, 'LineWidth', 2);
xlabel('Iteration');
ylabel('Best Val');
grid on;
```

- **DE Mutation**

```
function F=Mutate(x,mu,VarMin,VarMax)

   NVar=Numel(x);

   Nmu=ceil(mu*NVar);

   j=randsample(nVar,nmu);

   sigma=0.1*(VariaMax-VariaMin);

   F=x;
   y(:,:,j)=x(j)+sigma*randn(size(j));

   F=max(F,VariaMin);
   F=min(F,VariaMax);

end
```

- **DE Crossover**

```
function [a1, a2]=Crossover(b1,b2,gamma,VariaMin,VariaMax)

   alpha=unifrnd(-gamma,1+gamma,size(x1));

   a1=alpha.*b1+(1-alpha).*b2;
   a2=alpha.*b2+(1-alpha).*b1;

   a1=max(a1,VariaMin);
   a1=min(a1,VariaMax);
```

```
    a2=max(a2,VariaMin);
    a2=min(a2,VariaMax);

end
```

- **DE Selection**

```
function i=RouletteWheelSelection (F)

    R=rand;

    C=cumsum(F);

    i=find(R<=C,1,'first');

end
```